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Technical Report ARFSD-TR-89003

MASSIVELY PARALLEL IMAGE RECOGNITION SYSTEMS FOR REMOTELY SENSED DATA

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June 1989

U.S. ARMY ARMAMENT RESEARCH, DEVELOPMENT AND ENGINEERING CENTER

Fire Support Armament Center
Picatinny Arsenal, New Jersey

US ARMY
ARMAMENT MUNITIONS
& CHEMICAL COMMAND
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UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION UNCLASSIFIED	**1b. RESTRICTIVE MARKINGS**
2a. SECURITY CLASSIFICATION AUTHORITY	**3. DISTRIBUTION/AVAILABILITY OF REPORT** Approve for public release; distribution is unlimited.
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER Technical Report ARFSD-TR-89003	**5. MONITORING ORGANIZATION REPORT NUMBER)**
6a. NAME OF PERFORMING ORGANIZATION ARDEC, FSAC Fire Control Div. — **6b. OFFICE SYMBOL** SMCAR-FSF-RC	**7a. NAME OF MONITORING ORGANIZATION**
6c. ADDRESS (CITY, STATE, AND ZIP CODE) Picatinny Arsenal, NJ 07806-5000 (cont)	**7b. ADDRESS (CITY, STATE, AND ZIP CODE)**
8a. NAME OF FUNDING/SPONSORING ORGANIZATION ARDEC, IMD STINFO Br — **8b. OFFICE SYMBOL** SMCAR-IMI-I	**9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER**
8c. ADDRESS (CITY, STATE, AND ZIP CODE) Picatinny Arsenal, NJ 07806-5000	**10. SOURCE OF FUNDING NUMBERS** PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO. / WORK UNIT ACCESSION NO.

11. TITLE (INCLUDE SECURITY CLASSIFICATION)
MASSIVELY PARALLEL IMAGE RECOGNITION SYSTEMS FOR REMOTELY SENSED DATA

12. PERSONAL AUTHOR(S)
Manuel F. Tenorio, Purdue University, Frank P. Kuhl, ARDEC Project Engineer

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (YEAR, MONTH, DAY)	15. PAGE COUNT
Progress	FROM 12/87 TO 12/88	June 1989	21

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (CONTINUE ON REVERSE IF NECESSARY AND IDENTIFY BY BLOCK NUMBER)
FIELD	GROUP	SUB-GROUP	Neural networks Object recognition Vision systems

19. ABSTRACT (CONTINUE ON REVERSE IF NECESSARY AND IDENTIFY BY BLOCK NUMBER)

The design of classical vision systems is based on serially piecing together individual algorithms, each of which is intended to solve a specific part of the vision problem under a given set of assumptions. This has met with poor performance and low information throughput. The design process for each of these algorithms is usually disjoint, and ignores the system integration process. Speculation was made on a new philosophy for the design of vision systems that uses highly parallel and simple elements that are easily integrated. To improve the performance of the simple algorithms involved, heavy use of closed feedback loops is made throughout the system. These loops have self-correcting capabilities in different time scales. This work suggests a simple system that uses several of these concepts to perform multiple object recognition in noisy conditions.

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☐ UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT. ☐ DTIC USERS	**21. ABSTRACT SECURITY CLASSIFICATION** UNCLASSIFIED
22a. NAME OF RESPONSIBLE INDIVIDUAL I. HAZNEDARI	**22b. TELEPHONE (INCLUDE AREA CODE)** (201)724-3316 — **22c. OFFICE SYMBOL** SMCAR-IMI-I

DD FORM 1473, 84 MAR

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

6 NAME OF PERFORMING ORGANIZATION (cont)

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INTRODUCTION

The goal of designing computer vision algorithms for image recognition systems, broadly stated, is to produce automatic tools to acquire, manipulate, understand, and process imagery information, and through this, to identify the objects that generate such images. This goal is made difficult to achieve not only by the large amount of information contained in an image and the variability under which imagery data can be produced, but also by the number of different aspects that the same object can have in different images (ref 1). In an effort to understand these problems, researchers have isolated the details of the behavior of the particular components of an image recognition system, and studied them under controlled conditions. This has led to a number of image models, and a greater understanding of the physics of images. Another outcome of this effort was a large number of special purpose algorithms, capable of handling a limited array of image variations.

These stand-alone components introduced system integration problems; the components were designed with no knowledge about each other, and with expectations about the preceding and succeeding stages of the system which were not always satisfied. Therefore, with robustness as a paramount issue, the goal of total system integration has been a fleeting objective for the past 20 years, and it has become very clear that the components for an integrated system must adhere to standards of performance and robustness which make them computationally impractical, Not only do they require a large amount of hardware (both memory and computer power), but as the number of variations the system must handle is increased, so does the serial nature of the algorithms, removing the hopes of full parallel processing computation.

It was also clear from the lessons of Nature, that this trend was running contrary to the underlying theme seen in natural vision systems. The natural design, exposed by more recent neurophysiological research, is formed by simple, parallel, cooperating-competing systems. The natural design is also carefully harmonized with the environment of the animal and the purpose for which visual information is to be used. With the advent of more mature research into the architecture and the behavioral aspects of the visual nervious systems, an entirely new philosophy of image recognition system design could be embraced. This philosophy concentrated on the design of simple and massively parallel structures, with a simultaneous application of a set of mutally satisfying constraints over the entire image (ref 2). However, it was noticed that each individual algorithm resulting from this new philosophy did not perform as well as its more complex classical counterpart; not all image variations could be taken into consideration. To circumvent this problem, some assumptions needed to be made about the image. This was the same shortcoming present in the classical case. Nevertheless, the new design offered an unprecedented opportunity to circumvent this problem; the highly decentralized and parallel algorithms permitted mutal interaction and tuning. This allowed pursuit of designs that contain competing and cooperating algorithms; when an algorithm did not perform well under certain types of image variations, another was used (ref 3).

The information needed to hypothesize the properties of the image data could now be taken from the output of higher level components of the system. This permitted the initial estimates constantly to be refined throughout the processing time (resonance). The entire system became tightly connected and robust, although it still maintained basic simplicity and a high degree of parallelism.

DESIGN PROCEDURE FOR RESONATING ALGORITHMS

No matter how complex the algorithm, it can never be designed to successfully account for all possible aspect variations that an object can produce in real images. The more complete the algorithm, the more serial and computationally expensive it becomes. With complex imagery, there will always be cases that have not been considered. Since it is impossible to consider all cases beforehand, an alternative methodology is proposed that employs simple and robust parallel algorithms that are forced to interact according to a set of parallel multiple constraints (fig. 1).

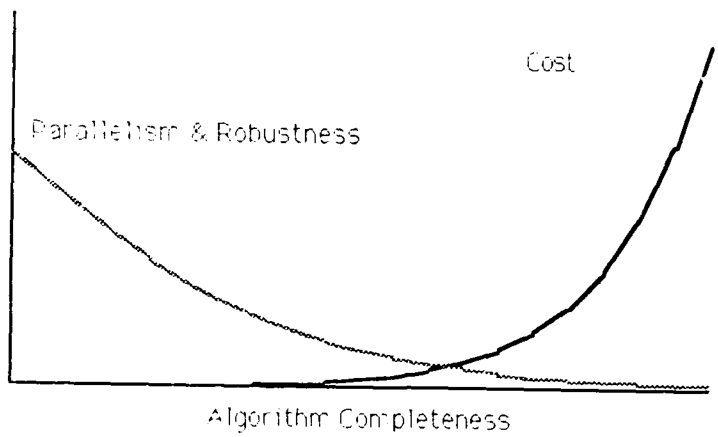

Figure 1. Cost and parallelism variation versus completeness

These algorithms are designed by stating the list of physical phenomena that give rise to important characteristics of the image and at the same time constrain the possible differences in object appearance. For example, if the object of interest is white, flies at near random patterns, and usually will be seen at night, then the algorithm would concentrate on detecting a bright pixel grouping which represents a discontinuity in the dark background in both time and space. Such constraints, once applied over the entire image, should cause automatic disregard of large fixed white backgrounds, speck size white patterns (e.g., sensor noise), and any other nonwhite region. A simple way to satisfy these constraints in parallel is to have every pixel check its value and the values of its neighbors in time and space. If the pixel finds itself with a white measurement surrounded by a dark background, it labels itself as background and discards the white

measurement as noise. If it has a white neighborhood but it is fixed in time, it also discards the measurement labeling itself as background. Only when it finds discontinuity in time with a consistent white neighborhood in space, does it take the label of an object of interest. The hypothesis created at this stage will be confirmed by later stages of processing. This type of constraint satisfaction problem has been demonstrated to be equivalent to resistive or simple nonlinear, uniform analog circuits.

The equations described by such a process as noncasual in both space and time. This suggests that a single pixel cannot definitely label itself until all other pixels are labeled in the image. To solve this problem, processing is done in stages. Initially, the pixels take an educated gues at their labels; then, competition allows for each pixel in parallel to look at its neighborhood and adjust its value. This process corresponds to a descent in the energy space of the system, settling down in the best compromise of all hypotheses (not necessarily the most optimum compromise). The final interpretation is said to resonate in the system, and the values of the pixel classification are said to be at a fixed point (this is the first type of resonance described) (fig. 2).

Notice that the design of such an algorithm could have benefited from another algorithm which would be carefully tuned to discern movement only with a certain range of speeds. This algorithm could pick up objects of interest by analyzing motion, and could be used to predict the future object position since it retains information about the trajectory. It would not be able to discern among objects of different colors in the same way tht the previous algorithm could not discern among slower or faster moving objects.

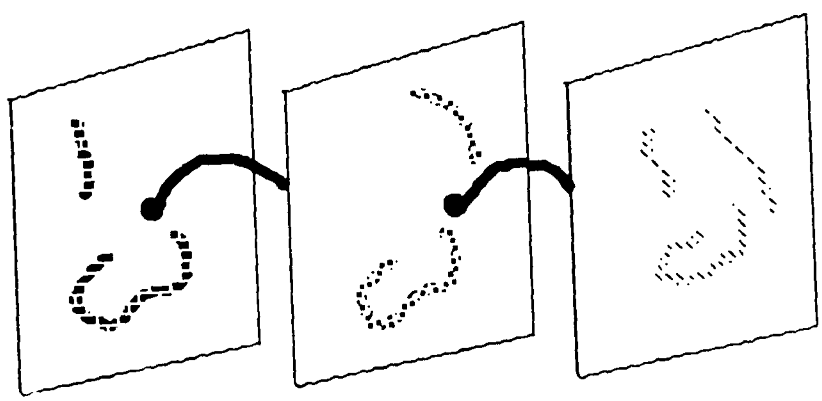

Figure 2. Intralevel resonance between algorithms

By combining the output of both algorithms, a better interpretation of the image could be achieved. In this particular case, after the internal resonance process, the algorithms would exchange and mutally reinforce areas of interest, based on how much they satisfy the constraints. This would allow the pixels another chance to review their labels based on additional information. This process is repeated until another resonant interpretation is found between the algorithms. Notice the much slow time scale of this second process. Both algorithms still retain the qualities of parallelism, falut tolerance, and simplicity.

A third level of processing is added to increase the level of confidence in the interpretation. The previous resonance pointed out the areas of interest in the image and produced a large reduction in the data set size. However, nothing was said about how bright algorithm 1 should expect the object to be, or about how fast algorithm 2 should [illegible]ect the object. Notice that if the interpretation is correct, the levels of confidence of [illegible] will increase, and the interpretation is said to be "locked" (they are mutally reinforced). If it is not, the process decreases the initial level of confidence, and if this process is repeated for a while, the interpretation confidence will drop below acceptable limits, and the region will be discarded as noise. This third type of resonance happens in a much slower time scale than the others, and it is responsible for removing ambiguities (fig. 3).

The third level can be used to finalize the interpretation by imposing additional "context" constraints to the previous results. Assume for example, that the object of interest has specific patterns on its back and it flies only in the forward direction. The presence of high level features can be used to confirm the object identification. A companion algorithm could take into account new hgih level features such as the position of fixed ligh sources, and adjust the expected brightness value in algorithm 1. If this interpretation is fed back to the lower levels, resonance of the third kind described takes place, further enhancing the interpretation.

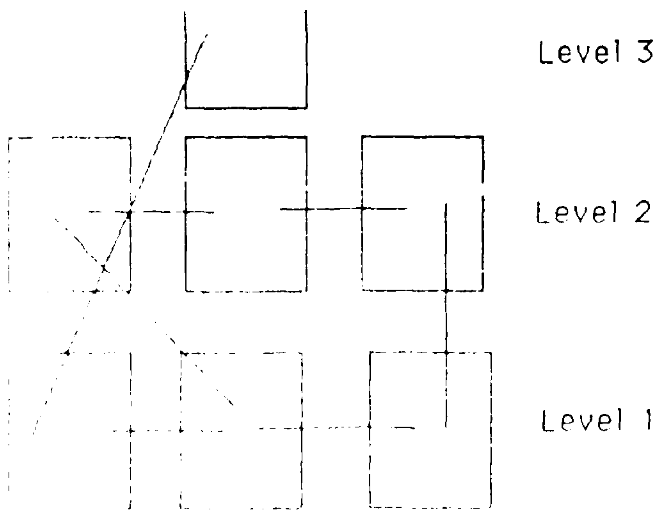

Figure 3. Interlevel resonance processes

The advantages of the separate modules as opposed to a monolithic design are simplicity, adaptability, parallelism, fault tolerance, and robustness. The first benefits are rather intuitive, and robustness reaiy illustrated. If the context is such that one of the modules is rendered useless, there is enough support from other constraints to make the correct interpretation (e.g., an object flying a straight collision course could render the speed detector useless but not the brightness detector). This kind of degenerate sitation is common in image interpretation system, and is the cause of the poor performance of integrated systems. The types of highly parallel algorithm with simple interconnecting elements as described here are known in the literature as connectionist algorithms or neural networks (refs 4 and 5).

SPECIAL PURPOSE FEATURE BASED SYSTEM

To understand these concepts further and to study the stability and effectiveness of the resonant mechanisms in a shape recognition problem, a simple but very useful simulation based on Fourier and moments descriptors was constructed. To decrease the computational load, the system was broken down into levels, each being responsible for abstracting the data sent to another level. The system was designed to cope with a large number of sensed images which differ both in spectra and in time. The system should be able to recognize objects of different classes, same class and multiple occurence, and multiple perspective, and it should handle large amounts of noise as well as shape occlusion.

The system consists of three levels: a segmentation level, a feature extraction level, and an object classification level (fig. 4). The segmentation level, although being general, can enhance its performance with the knowledge obtained about object identification, position, and orientation. Object identification information is provided by the tope level which works as an heteroassociative bidirectional memory (ref 6). The second level receives the segmented image and proceeds to extract features. It is also capable of receiving the correct feature set, and reversing it to produce a model image that can then be adjusted to match the input image. The top level, after receiving a feature vector with noise, produces a nearest neighbor classification of it, and as the output of the associative memory, gives information to the first level about the classification for parametric tuning. Since it is a bidirectional memory, it alters the feature vector to match the classifier interprettion; this, in turn, forces the second level to correct pixels misclassified by the first level (i.e., occluded pixels). This entire process works on the resonance principles described above (fig. 4).

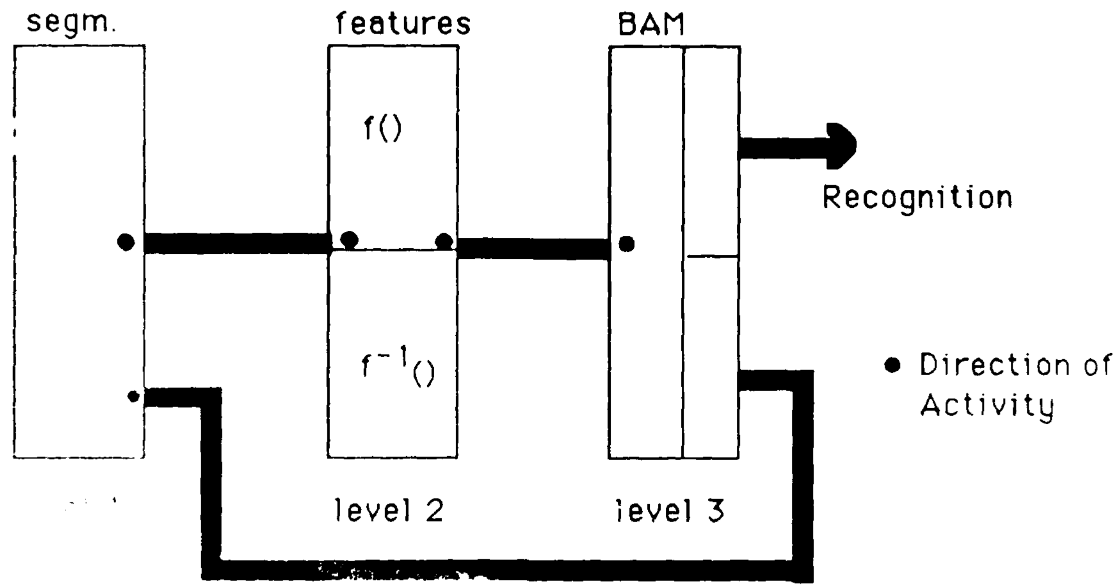

Figure 4. Diagram of the shape recognition system

Segmentation Algorithm

The segmentation algorithm is responsible for filtering out possible objects in the image for final interpretation. To proceed in our design, let's define a set of physical constraints to construct the segmentation algorithm at the first level. For the sake of simplicity in our discussion, only the following two assumptions about the objects were made.

1. Homogeneity: every object of interest is made of the same material and, therefore, should produce similar visual results.

2. Continuity: every object of interest is, for the most part, solid and, therefore, should appear in closed neighborhoods.

These two assumptions are fairly general, and they hold in a variety of situations, except at the boundary pixels of our objects as will be seen in the example. The mathematical model that has given rise to the study of spatially dependent phenomena in regular neighborhoods is called Markov Random Fields, and it will be used tomodel the continuity assumption. If a certain range of brightness values is accepted as representative of the material characteristics, a likelihood function is a good candidate for the model (refs 7 through 11).

Problem Formulation

The problem of segmentation is defined as grouping parts of a generalized image into regions, homogeneous with respect to some characteristics or features and resulting in a partitioned image (refs 9, 10 and 12 through 14).

Define a picture $F = f(x,y)$ as a two dimensional intensity function $f(x,y)$. The quantized version of $f(x,y)$ in both spatial coordinates and intensity is denoted by the matrix $G = [g_{ij}]$ ($N_1 \times N_2$). F is composed of M different regions (which can occur an arbitrary number of times each), and through the use of different sensors, K distinct images $\{G_k\}_k = 1..K$ of the same scene can be obtained.

Also, assume that each element $g^k ij$ is actually the sum of $b^k ij$ and $\eta^k ij$ and pixel (i,j) being in region m through observation k

$$g^k ij = b^k ij + \eta^k ij \tag{1}$$

where $\{b^k ij\}$ and $\{\eta^k ij\}$ are stochastic fields characterizing the underlying scene, and the observation noise, respectively, in the data set k. A further simplifying assumption is made: each region type m in each data set k can be characterized by a constant *intensity, $r^k m$, which is the mean of that region* (i.e., $b^k ij = r^k m$), if the pixel (i,j) region type m. Furthermore, the additive noise field $\eta^k ij$ is assumed to be spatially uncorrelated and Gaussian so that the vector of the observation noise

$$\eta_{ij} = [\eta^1 ij, \eta^2 ij, \ldots, \eta^K ij]^T \tag{2}$$

is a multivariate normal with mean zero and covariance matrix C_m in region m. This implies that the observation vector

$$g_{ij} = [g^1 ij, g^2 ij, \ldots, g^K ij]^T \tag{3}$$

is a multivariate normal with mean r_m

$$r_m = [r^1 m, r^2 m, \ldots, r^K m]^T \tag{4}$$

and covariance C_m, if pixel (i,j) is in region type m

The segmentation problem can be stated as mapping G into a matrix B^ [illegible] from an estimate S^ of the sets $S = \{S_m\}$ m = 1...M where

$$S_m = \{(i,j): b^k ij = r^k m\} \tag{5}$$

$$B^\wedge = [b^\wedge ij]\ (N_1 \times N_2): b^\wedge ij\ \varepsilon\ [1 \ldots M] \text{ and } b^\wedge ij = m \text{ iff } (i,j)\ \varepsilon\ S_m \tag{6}$$

meaning, $B^\wedge$ is an M-level image matrix, where $b^\wedge ij = m$ if S_m contains pixel (i,j).

Using the classical maximum likelihood segmentation method, define:

$$p_m(x) = (2\pi)^{K\,2}|C_m|^{-1\,2}\exp[(x - r_m)^T C^{-1}\, m\, (x - r_m)] \tag{7}$$

The segmentation procedure will assign pixel (i,j) to region set S_m if

$$p_m\,(g_{ij}) >= p\,(g_{ij}) \text{ and } 1 =< l =< M \tag{8}$$

This method only works well if the signal-tonosie ratio is $s/n\ \Xi\ \Delta/\sigma$, where $\Delta\ \Xi\ r_1 - r_2$.

To develop a more robust procedure, it is necessary to bring other constraints into the model. In this case, it is assumed that solids objects will appear in connected blobs or subsets. At the pixel level, this would imply that for (i,j) to belong to region m

$$b^\wedge_{ij} = m \rightarrow \{\ni|b_{i+\varepsilon,j+\varepsilon}: b_{i+\varepsilon,j+\varepsilon} = m \wedge \varepsilon\ E\ \{-1, 0, 1\}, (i+\varepsilon, j+\varepsilon)\ (i,j)\} \tag{9}$$

This can be modeled by a Markov field with 8-nearest neighbors defining the process support. Assuming this limited support, the Markov process can be characterized by the transition probabilities

$$\begin{aligned} &p(b^k ij = r^k m,\ 1 =< k =< K \mid b^k rs \\ &\qquad 1 =< r =< N_1,\ 1 =< s =< N_2 \\ &\qquad\qquad (r,s) \neq (i,j),\ 1 =< k =< K) = \\ &p(b^k ij = r^k m,\ 1 =< K =< K \mid b^k rs\ (r,s)\ \varepsilon\ \delta_{ij},\ 1 =< k =< K) = \\ &P_{ijm} \end{aligned} \tag{10}$$

where δ_{ij} is the local neighborhood of pixel (i, j) as in equation 9. The segmentation problem can now be formulated as a maximum A posteriori probability (MAP) estimation problem. In particular, let l(.) represent a log-likelihood function. We would then like to find the estimate S′ which maximizes the conditional likelihood

$$l(S'|G) = l(G|S') + l(S') - l(G) \tag{11}$$

or since I(G) is independent of S^, more simply we can minimize

$$1(S\text{^},G) = 1(G/S\text{^}) + 1(S\text{^}) \tag{12}$$

In this case,

$$1(G/S\text{^}) = \Sigma^{M}_{m=1} \Sigma_{(i,j)\varepsilon s_m} 1n\{p_m (g_{ij})\} \tag{13}$$

and

$$1(S\text{^}) = \Sigma^{M}_{m=1} \Sigma_{(i,j)\,\varepsilon\, S_m} 1n\{P_{ijm}\} \tag{14}$$

where p_m and P_{ijm} are defined in equation 8 and 10, respectively.

The solution to this equation can be found in parallel, by applying these constraints to all the pixels of the image, which have been utilized with the brightness value of each point. The relaxation process that follows decreases the overall energy of the sytem by modifying each individual pixel classification, or the sets $S = \{S_m\}$ m=1...M (refs 13 and 14). Similar equations have also been the motivation for optimization in such relaxation lattices (refs 15 through 18).

An airplane image 512 x 480, subject to glare, noise, and a nonuniforfm background is shown in figure 5. Using simply the constraints above, the parallel implementation of the segmentation algorithm relaxes to the interpretation given in figure 6. Notice that only the first king of resonance is at work, and that the constraints are extremely simple. More sophisticated schemes are capable of handling textures during the segmentation process (ref 19).

FEATURE EXTRACTION WITH CONNECTIST MODELS

There has been a considerable amount of work done on shape encoding and recognition using moments and Fourier descriptors (refs 20 through 28). The decision to use such models was based on the fact that this procedure is simple and well understood, and can be made reversible.

In this system, the feature extractor module receives a portion of the image from the segmentor. This image portion contains only the labels of the pixels and not the pixel values themselves (fig. 4). The module then applies a transformation to the image and produces at the output the important features to describe the object. The choice of the set of transformations and features can be made abitrarily complex, but for the sake of simplicity, only the Fourier descriptor method is discussed.

Fourier Descriptor Method

There are two ways of designing a high parallel, feature-based module. (1) The more classical methods of extracting parallelism from a given algorithm can be applied. The dataflow graph of the algorithm is created, a careful investigation of the application of various transformations is made, and the resulting data flow graph is compared for parallelism and speedup (i.e., increased breadth and reduced depth of the graph). After the final transformation, the algorithm is hardwired into the computer architecture. (2) A less traditional and perhaps more interesting approach is to take advantage of the adaptive characteristic of connectionist models. There, we start with the parallel model, and using a learning algorithm, adapt the system until the cohort of elements produces the desired transform. This model sometimes leads to approximations of the original transforms due to the need for limiting the number of processors used. Besides leading to good approximations in most cases (ref 29), our application can make good use of this adaptive method since, on a practical implementation, even the successful traditional transform designs would also be subject to approximation and truncations (ref 28).

With this adpative method, an inverse transform module, which would feedback the correct pixel classification to the segmentation unit after recognition can be designed. It is important to be able to reconstruct the original image after recognition for a variety of reasons. Perhaps, the most important one is the ability to deal with multiple objects and occlusions. This works as follows: Assume that the segmentation algorithm can separate the image into several different sets of pixels according to some homogenity criteria. The identification system would be more sensitized by the object which is the largest or with least amount of occlusion, the least noisy, or the least ambiguous. After the identification is correctly done, the system can send an inhibitory signal to all the pixels that participate in that object, and it would be free to pick up the next prominent available object even if it was partially occluded by the first. In this global serial mode, the system proceeds to identify each class of pixels, one at a time, through the same resonating scheme.

Fourier and moments methods have been shown to deal extremely well with object recognition at varying 3-D perspective, producing not only the recognition of the object but the orientation (ref 28). In the same reference, the two methods are compared with other methods, such as range moments. Fourier and moments methods can be made invariant to position, rotation, and scaling by adding the proper modifications. Although this property is valuable during the classification process, it is necessary for a quick reconstruction of the image to preserve information about these varying attributes. For example, a position invariant transformation generates features that, when inverted, can have several interpretations in the image. To solve this problem, the value of the

centroid of the region and the angle of its main axis can be retained as one of the features. These features would aid the inverse transformation in the pixel inhibiting operation.

Adaptive Methods for Feature Extraction

If it is desired to design even more sophisticated models of feature extraction and use the features to describe object identification, orientation, and absolute and relative positions, the adaptive qualities ofthe connectist models can be used again. One of the classes of adaptive algorithms is called supervised learning. The most popular of such algorithms for highly parallel networks is called the Generalized Delta Rule (Ref 4). The user provides the network with a careful choice of examples accompanied by the desired response of the system. The network proceeds to alter its parameters until the desired transfer function can be emulated. Mathematical studies of such a model have shown that unlimited networks can approximate an arbitrary function arbitrarily close. These issues are beyond the scope of this work.

BIDIRECTIONAL ASSOCIATIVE MEMORIES

The highest module in this identification system is the bidirectional associative memory. It doubles as a nearest neighbor classifier and a library look up, but because of its parallel structure, can do both very efficiently. There are two characteristics to the design of such a memory that appeal to this problem: (1) It can deal with noise corrupted features very well, even in the presence of hardware damage and (2) it uses a resonating structure (heteroassociative) which recalls related information to the input, uses this new information to correct the input, and then reuses the new input for recall. This process continues until a perfect match is found.

There are severalways that this type of memory could be constructed. The first to suggest a possible design was Bart Kosko (ref 6). This design displays all the desirable characteristics discussed above. One major drawback that has driven the research in this area is the storage capacity of such memories (ref 30). The number of possible patterns is less than the sum of the lengths on the input and output feature vectors. After this number, the meory tends to generalize and fuse patterns together and somestimes generate spurious memories, combinations of other recalls.

Basically, Kosko's memory works through the following computation: Let A be the input feature vector, and B be the associated output vector. When A is received, a multiplication of A by a matrix M is performed to generate B. M represents the long term storage memory of the system. Once B is obtained, a multiplication of B with M^1 is performed to generate A. If A is corrupted with noise, then the recalled version of B would be also corrupted. This bidirectional process would continue until the system is capable of genrating A and B (stable memory points). Notice that a more daring design

could couple several of these modules forming a close cicuit where each module would perform one type of association. This could have a significant impact on the performance of the pattern recognition system. When a good discrimination cannot be done in any of the individual feature spaces, it might be possible through evidence accumulation on several spaces.

CONCLUSIONS

The implications of a parallel connectionist-like design for vision system has been discussed. In particular, the design of a simple object recognition system based on resonant principles. This design should allow us to tackle problems of noise, occlusion, and ambiguity in a fresh new light, making heavy use of tightly coupleo continuous feedback systems for vision. In particular, the implementation of each module is parallel and simple. The strength of the design is derived from the combination of modules and the resonant structures.

Some research questions, with great impact to the engineering of such systems, still remain to be answered: (1) To what degree and under what circumstances is this system stable, given all the feedback loops? (2) How can bidirectional memories be designed with very large sotrage capacity to address the vision problem? Nevertheless, the preliminary results are promising, and the possibilities for designing vision systems using this technology indicate that it might soon challenge classical systems in speed, fault tolerance, and performance.

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